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Temporal and spatial responses of ecological resilience to climate change and human activities in the economic belt on the northern slope of the Tianshan Mountains, China

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Abstract: In the Anthropocene era, human activities have become increasingly complex and diversified. The natural ecosystems need higher ecological resilience to ensure regional sustainable development due to rapid urbanization and industrialization as well as other intensified human activities, especially in arid and semi-arid areas. In the study, we chose the economic belt on the northern slope of the Tianshan Mountains (EBNSTM) in Xinjiang Uygur Autonomous Region of China as a case study. By collecting geographic data and statistical data from 2010 and 2020, we constructed an ecological resilience assessment model based on the ecosystem habitat quality (EHQ), ecosystem landscape stability (ELS), and ecosystem service value (ESV). Further, we analyzed the temporal and spatial variation characteristics of ecological resilience in the EBNSTM from 2010 to 2020 by spatial autocorrelation analysis, and explored its responses to climate change and human activities using the geographically weighted regression (GWR) model. The results showed that the ecological resilience of the EBNSTM was at a low level and increased from 0.2732 to 0.2773 during 2010–2020. The spatial autocorrelation analysis of ecological resilience exhibited a spatial heterogeneity characteristic of "high in the western region and low in the eastern region", and the spatial clustering trend was enhanced during the study period. Desert, Gobi and rapidly urbanized areas showed low level of ecological resilience, and oasis and mountain areas exhibited high level of ecological resilience. Climate factors had an important impact on ecological resilience. Specifically, average annual temperature and annual precipitation were the key climate factors that improved ecological resilience, while average annual evapotranspiration was the main factor that blocked ecological resilience. Among the human activity factors, the distance from the main road showed a negative correlation with ecological resilience. Both night light index and PM2.5 concentration were negatively correlated with ecological resilience in the areas with better ecological conditions, whereas in the areas with poorer ecological conditions, the correlations were positive. The research findings could provide a scientific reference for protecting the ecological environment and promoting the harmony and stability of the human-land relationship in arid and semi-arid areas.

Keywords: ecological resilience; ecosystem habitat quality; ecosystem landscape stability; ecosystem service value; spatial autocorrelation analysis; geographically weighted regression model; economic belt on the northern slope of the Tianshan Mountains

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1 Introduction

Since the Earth entered the Anthropocene era, human activities have gradually become complicated and diversified and have developed drastically, becoming the main driving force of ecological environmental change (Crutzen, 2002; Waters et al., 2016). The structure and functions of the ecosystems have changed and reshaped, and ecological problems (such as environmental pollution, water resource shortages and biodiversity loss) have become prominent. Regional ecosystem is subjected to unavoidable disturbance and impact, and the pressure to resist uncertain risks is gradually increasing (Rapport, 2007; Sachs et al., 2022). The topic of dealing with various ecological crises and challenges has attracted wide attention from various countries and regions (Pendall et al., 2009; Peng et al., 2017). Resilience theory provides a new research perspective for solving this problem (Cai et al., 2012; Peng et al., 2017). Holling (1973) applied the concept of resilience to ecology for the first time in the 1970s and pioneered the study of modern resilience theory, which has been widely used in urban and regional studies (Jabareen, 2013; Nyström et al., 2019). Most researchers agree that the capacity for a system to actualize self-recovery and maintain its stability when confronted by an external disruption or crisis is the core definition of resilience (Alberti and Marzluff, 2004), and a system with high resilience can recover continuously after system damage through three kinds of abilities: resistance, recovery and adaptability (Alberti and Susskind, 1996; Maguire and Hagan, 2007; Frommer, 2013; Chen et al., 2020).

As an important dimension of regional resilience research, ecological resilience has become a hot topic and is an important means for promoting the balance and stability of regional ecosystems (Holling, 1973; Schulze, 1996; Adger, 2000). The existing research focused on the assessment and optimization of ecological resilience, and the selection and construction of scientific assessment models and methods are the key to conduct research on ecological resilience (Liu et al., 2020; Zhao et al., 2021). At present, a research system of ecological resilience has been formed, which is dominated by the comprehensive index method (Xiao et al., 2020; Zhao et al., 2021; Li et al., 2023), function model method (Li and Liu, 2022; Shi et al., 2022; Xia et al., 2022), network model method (Hong et al., 2022; Huang et al., 2022) and scenario analysis method (Cumming et al., 2005), covering multiple perspectives such as vegetation cover (He et al., 2021; Qin et al., 2021), bearing state (Zhao et al., 2021), landscape pattern (Ortega et al., 2020), ecological network (Wang et al., 2021; Huang et al., 2022) and ecological security status (Yuan et al., 2022). In addition, exploring the relationship between ecological resilience and human activities from the perspectives of land use patterns (Colding, 2007), urbanization (Wang et al., 2022), and resource exploitation and utilization (Xiao et al., 2020) is also a focus of relevant research. It is generally believed that under the interference of economic growth, technological advancement, policy changes and other human activities, the internal structure and feedback mechanisms of ecosystems are gradually altered, and the uncertainty factors affecting ecological resilience have increased (Ernstson et al., 2010; Mao et al., 2019; Meng et al., 2022; Reader et al., 2023), seriously threatening the healthy development of regional ecosystems.

Approximately 41% of the world's surface is composed of arid and semi-arid areas (Gaur and Squires, 2018), and approximately 53% of the total land in China is arid and semi-arid land (Huang et al., 2019). The arid and semi-arid areas in Northwest China have entered a period of rapid development, with accelerated urbanization and industrialization, which significantly improved social and economic development (Fang, 2019). However, the expansion of urban and artificial oasis areas and the intensification of land use have led to the deterioration of habitat quality, water resource shortages, environmental pollution and other ecological and environmental problems (Deng et al., 2010; Ha and Kasimu, 2015; Wang et al., 2018; Zhang et al., 2023). In addition to being impacted by human activities, arid and semi-arid areas are still highly sensitive to climate

change (Wang and Qin, 2017; Chen et al., 2019). Climatic conditions such as precipitation, temperature and evapotranspiration determine the basic characteristics of ecological background conditions such as vegetation cover, material cycle and biodiversity (Kim et al., 2013; Valayamkunnath et al., 2018; Guo et al., 2021). At present, numerous studies have been conducted on ecological environment quality evaluation (Yan et al., 2021), resource and environment carrying capacity evaluation (Gao et al., 2021; Han et al., 2022), ecosystem services (Zhang et al., 2022; Hu et al., 2023), ecological security patterns (Pan et al., 2022a) and human-land system coupling coordination (Zhu et al., 2023) to seek a sustainable development path. However, most relevant studies ignored the assessment of ecosystem resilience and risk management in arid and semi-arid areas, and focused more on the health status of ecosystems than on the sustainability of ecosystems in response to various risks. It is particularly significant to comprehensively explore how ecological resilience in arid and semi-arid areas responds to increasingly complex human activities from the perspectives of climate change and human activities.

The economic belt on the northern slope of the Tianshan Mountains (EBNSTM) is located in arid and semi-arid areas of Northwest China, and is an important region leading the high-quality development of the core area of the Silk Road Economic Belt. Additionally, the EBNSTM is the most highly developed area in Xinjiang Uygur Autonomous Region, China for new-type industrialization, agricultural modernization and informatization (Lei et al., 2006; Xie et al., 2017; Deng, 2020). The EBNSTM achieved rapid development from 2010 to 2020, with urbanization rate, economic aggregate and built-up area increasing rapidly (Wang et al., 2023; Yang et al., 2023b). Human activities such as agricultural production, land reclamation, industrial development, resource extraction and urban construction are particularly intense in this region. The intense human activities and sensitive ecological environment have made the ecological and environmental problems of the EBNSTM increasingly apparent, such as the encroachment of ecological land, the degradation of habitat quality and the reduction of biological resources, resulting in increasing pressure and impact on the ecosystem and prominent contradiction between human and land resource. It is urgently to enhance the ecological resilience in this region to ensure the regional sustainable development.

Therefore, this study selected the EBNSTM as the research area and divided it into 5058 evaluation units using the 10 km×10 km grid. The ecological resilience index of each evaluation unit was calculated by using the ecological resilience assessment model constructed from three aspects of resistance, recovery and adaptability. Then, the temporal and spatial variation characteristics of ecological resilience in the EBNSTM during 2010–2020 were analyzed, and the responses of ecological resilience to climate change and human activities were explored using the geographically weighted regression (GWR) model. The findings can help to understand the resistance, recovery and adaptability of ecosystems in the region when responding to risks, and provide a reference for enhancing the ecological resilience and promoting harmonious coexistence between human beings and land resource in arid and semi-arid areas.

2 Materials and methods

2.1 Study area

The EBNSTM (79°88′–96°38′E, 40°87′–47°15′N) is located in Xinjiang Uygur Autonomous Region, China, bordering the Tianshan Mountains in the south and the Junggar Basin in the north. It contains Urumqi City, Karamay City, Turpan City, Hami City, Changji Hui Autonomous Prefecture, Bortala Mongolian Autonomous Prefecture, Tacheng Prefecture, counties (cities) direct under Ili Kazak Autonomous Prefecture and all the cities of Xinjiang Production and Construction Corps (Fig. 1), covering a total area of 4.79×10^5 km^2. The ecosystems here consist of mountains, oases and deserts, with a typical arid and semi-arid climate. Water resource shortages, limited ecological carrying capacity and fragile ecological environment are the main ecological problems in this region.

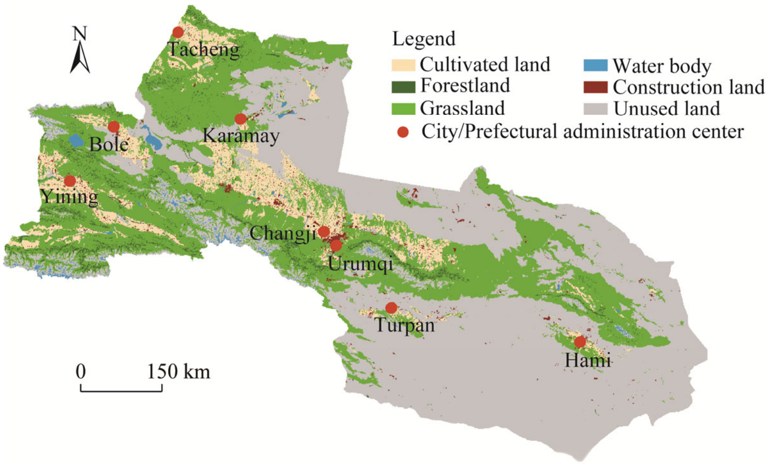

Fig. 1 Overview of the economic belt on the northern slope of the Tianshan Mountains (EBNSTM) and spatial distribution of land use types in 2020

2.2 Data sources

In this study, we collected geographic data (including land use data, road network data, night light index (NLI), annual precipitation (PRE; mm), average annual temperature (TMP; °C) and average annual evapotranspiration (ETP; mm)) and statistical data (including crop sown area (hm^2), grain yield (kg) and agricultural product price (CNY/kg)) in 2010 and 2020 to explore the responses of ecological resilience to climate change and human activities (Table 1). The classification criteria of land use types were referred to the land use data classification system of the Resource and Environment Science and Data Center (https://www.resdc.cn/). This study involved 6 first-level classes and 24 second-level classes of land use types (Table 2). We calculated TMP and ETP based on original monthly datasets. The statistical data were obtained from the Statistical Yearbook of Xinjiang Uygur Autonomous Region (Statistic Bureau of Xinjiang Uygur Autonomous Region, 2010–2020) and the China Yearbook of Agricultural Price Survey (National Bureau of Statistics, 2010–2020).

Table 1 Geographic data and statistical data used in this study as well as their sources

Data	Unit	Resolution (km)	Data source
Land use	/	1	Resource and Environment Science and Data Center (https://www.resdc.cn/)
TMP	°C	1	National Earth System Science Data Center (http://www.geodata.cn/)
PRE	mm	1	National Earth System Science Data Center (http://www.geodata.cn/)
ETP	mm	1	National Earth System Science Data Center (http://www.geodata.cn/)
Road network	/	/	Open Street Map (https://www.openstreetmap.org/)
NLI	/	1	Global Change Research Data Publishing & Repository (http://www.geodoi.ac.cn/)
Crop sown area	hm^2	/	Statistic Bureau of Xinjiang Uygur Autonomous Region (http://tjj.xinjiang.gov.cn/)
Grain yield	kg	/	Statistic Bureau of Xinjiang Uygur Autonomous Region (http://tjj.xinjiang.gov.cn/)
Agricultural product price	CNY/kg	/	National Bureau of Statistics (http://www.stats.gov.cn/)

Note: / indicates that the data do not involve resolution or unit. TMP, average annual temperature; PRE, annual precipitation; ETP, average annual evapotranspiration; NLI, night light index.

Table 2 First-level classes and second-level classes of land use types

First-level class	Second-level class
Cultivated land	Paddy field and dryland
Forestland	Forest, shrubbery, open forestland and other forestland
Grassland	High coverage grassland, medium coverage grassland and low coverage grassland
Water body	River canal, lake, reservoir pond, glacier and shoaly land
Construction land	Urban land, rural residential land and other construction land
Unused land	Desert, Gobi, saline and alkaline land, marsh, bare land, bare rock land and other unused land

This paper comprehensively considered the factors influencing ecological resilience and the applicability of data, and selected two types of influencing factors (climate and human activities) to explore the responses of ecological resilience in the EBNSTM.

PRE, TMP and ETP were the factors used to characterize the climate (Fig. 2). PRE reflects the degree of dryness and wetness and is the most direct factor affecting regional hydrological conditions (Liu et al., 2023). TMP reflects the temperature condition in the region, and the temperature level has a significant impact on soil microbial activities and vegetation growth (Guo et al., 2022). ETP reflects the evapotranspiration capacity of the underlying surface determined by climatic conditions; it can change water vapor exchange capacity and process between land surface and atmospheric environment (Valayamkunnath et al., 2018).

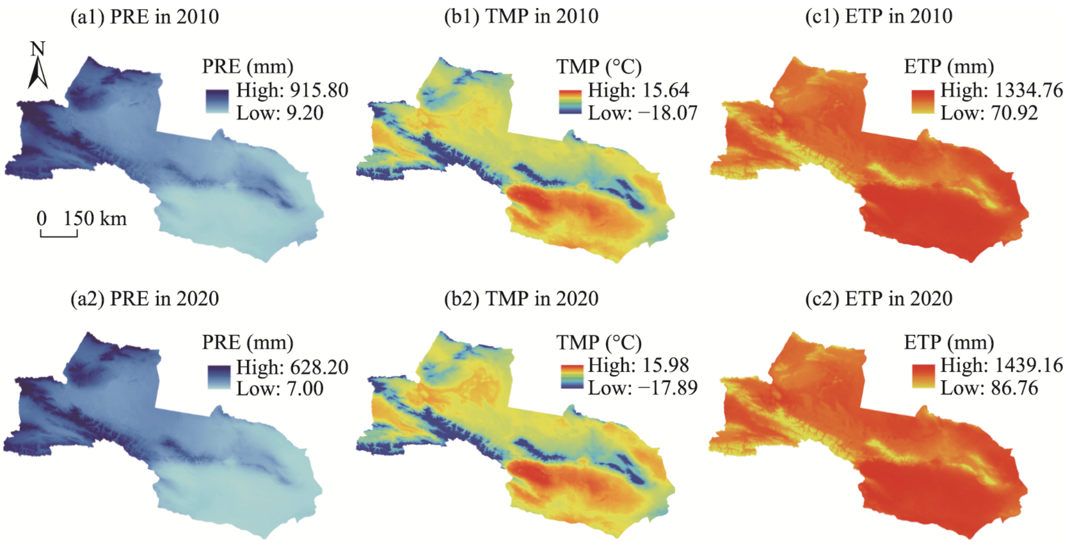

Fig. 2 Spatial distribution of PRE (a1 and a2), TMP (b1 and b2) and ETP (c1 and c2) in the EBNSTM in 2010 and 2020. PRE, annual precipitation; TMP, average annual temperature; ETP, average annual evapotranspiration.

Distance to the main road (MRD; km), NLI and PM2.5 concentration (μg/m^3) were the factors used to characterize human activities (Fig. 3). MRD represents the distance from human activities; the greater the value is, the weaker the interference by human activities is (Fu et al., 2019; Yang et al., 2023a). NLI represents the intensity of social and economic activities; the higher the value is, the more vigorous the social and economic activities are (Li et al., 2013). PM2.5 concentration is positively correlated with industrialization, which can characterize the level of regional industrialization (Zhang et al., 2020a).

2.3 Ecological resilience assessment model

Ecological resilience consists of resistance, recovery and adaptability (Alberti and Susskind, 1996; Maguire and Hagan, 2007; Frommer, 2013; Chen et al., 2020). Resistance is the ability of

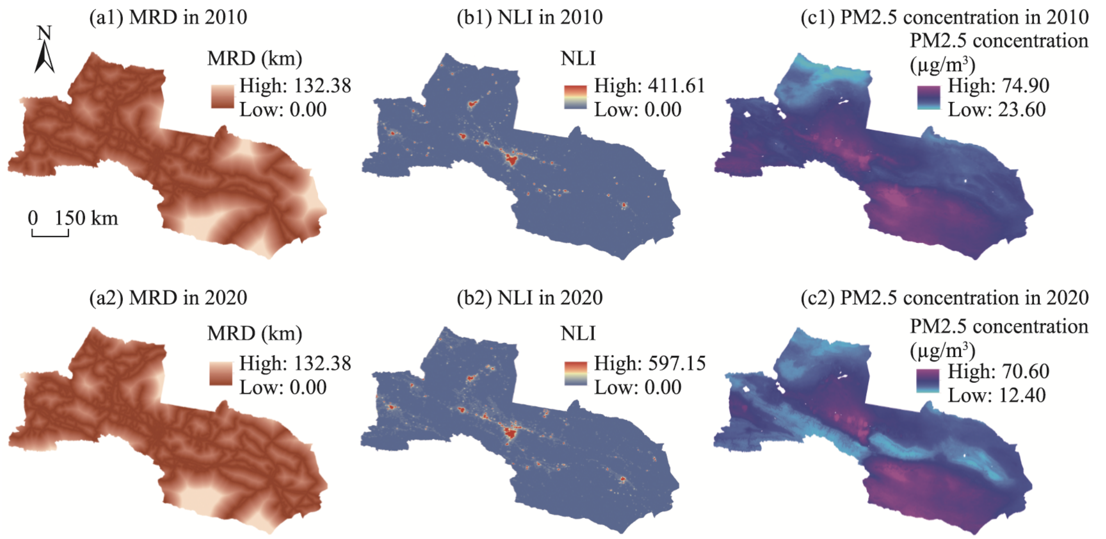

Fig. 3 Spatial distribution of MRD (a1 and a2), NLI (b1 and b2) and PM2.5 concentration (c1 and c2) in the EBNSTM in 2010 and 2020. MRD, distance to the main road; NLI, night light index.

ecosystems to resist all kinds of disturbances (Frommer, 2013), which is determined by the ecological background (Duo et al., 2022; Tong et al., 2023). Ecosystem habitat quality (EHQ) reflects the biodiversity and environmental quality of the natural background (Fahrig, 2003; Hillard et al., 2017); it can thus represent the resistance of ecosystems. Recovery determines how well the regional ecosystem can absorb external disturbances, which is used to buffer the pressure on the ecological environment and maintain the ability of the ecological environment to continue to recover (Frommer, 2013; Peng et al., 2017). Ecosystem landscape stability (ELS) is an important surrogate index reflecting ecosystem stability (Durilová and Saksa, 2003; Peng et al., 2015); the more stable the ecosystem is, the stronger its recovery will be. Adaptability is the ability of ecosystems to transform after resolving external risk disturbances and to support human development (Peng et al., 2017; Chen et al., 2020). Ecosystem service value (ESV; CNY/hm^2) is the benefit that human beings obtain through the material cycle and function running process of ecosystems; it is the service provided by ecosystems to maintain human survival and regional development (Braat and de Groot, 2012) and can be used as a parametric alternative indicator to characterize the adaptability of the ecosystem.

According to the analysis above, EHQ, ELS and ESV could be used to represent resistance, recovery and adaptability, respectively. Then, we constructed an ecological resilience assessment model according to relevant studies (Li and Liu, 2022; Shi et al., 2022; Xia et al., 2022), and the formula is as follows:

$$\mathrm{ER} = (\mathrm{EHQ} + \mathrm{ELS} + \mathrm{ESV}) / 3\,, \tag{1}$$

where ER represents the ecological resilience; EHQ is the ecosystem habitat quality, representing ecosystem resistance; ELS is the ecosystem landscape stability, representing ecosystem recovery; and ESV is the ecosystem service value, representing ecosystem adaptability.

Evaluation unit division is an important step both in ecological resilience evaluation and spatial visualization. In order to scientifically and reasonably characterize the spatial distribution characteristics of ecological resilience on the grid scale, we divided the study area into 5, 10, 15 and 30 km grids for test and comparison, and found that it was more reasonable to use 10 km grid scale to divide the study area. Therefore, we divided the study area by 10 km×10 km grids. After obtaining the data of indicators (EHQ, ELS, and ESV) on each grid of the EBNSTM in 2010 and 2020, we standardized each indicator to eliminate the dimensional relationship between variables. Finally, the standardized data of each indicator were substituted into Equation 1 to obtain ecological resilience data on the 10 km grid scale.

2.3.1 Assessment of ecosystem habitat quality (EHQ)

In this study, the Integrated Valuation of Ecosystem Services and Tradeoffs (InVEST) model (McKinney, 2002) was used to evaluate the EHQ of the EBNSTM. Habitat suitability and sensitivity, threat factors and their impact distances are the key parameters of this model. Habitat suitability refers to the suitability of each land use type as a habitat, and it is generally believed that the closer the land use type is to nature, the higher the habitat suitability is. Threat factor setting mainly considers the disturbance degree of land use type to habitat, and the higher the intensity of land use is, the greater the threat degree to habitat is. This study selected cultivated land, urban land, rural residential land and other construction land as threat factors. The sensitivity of a habitat to threat factors mainly depends on the complexity of the habitat ecosystem; generally, the more complex the ecosystem is, the lower its sensitivity to various threat factors is. The value ranges of habitat suitability and sensitivity are all from 0.00 to 1.00. The parameters for the InVEST model were set by consulting the existing research results in similar areas (Bai et al., 2019; Wei et al., 2022a; Wei et al., 2022b; Zhao et al., 2022), and EHQ in 2010 and 2020 was calculated and standardized (Fig. 4a1 and a2; Tables 3 and 4).

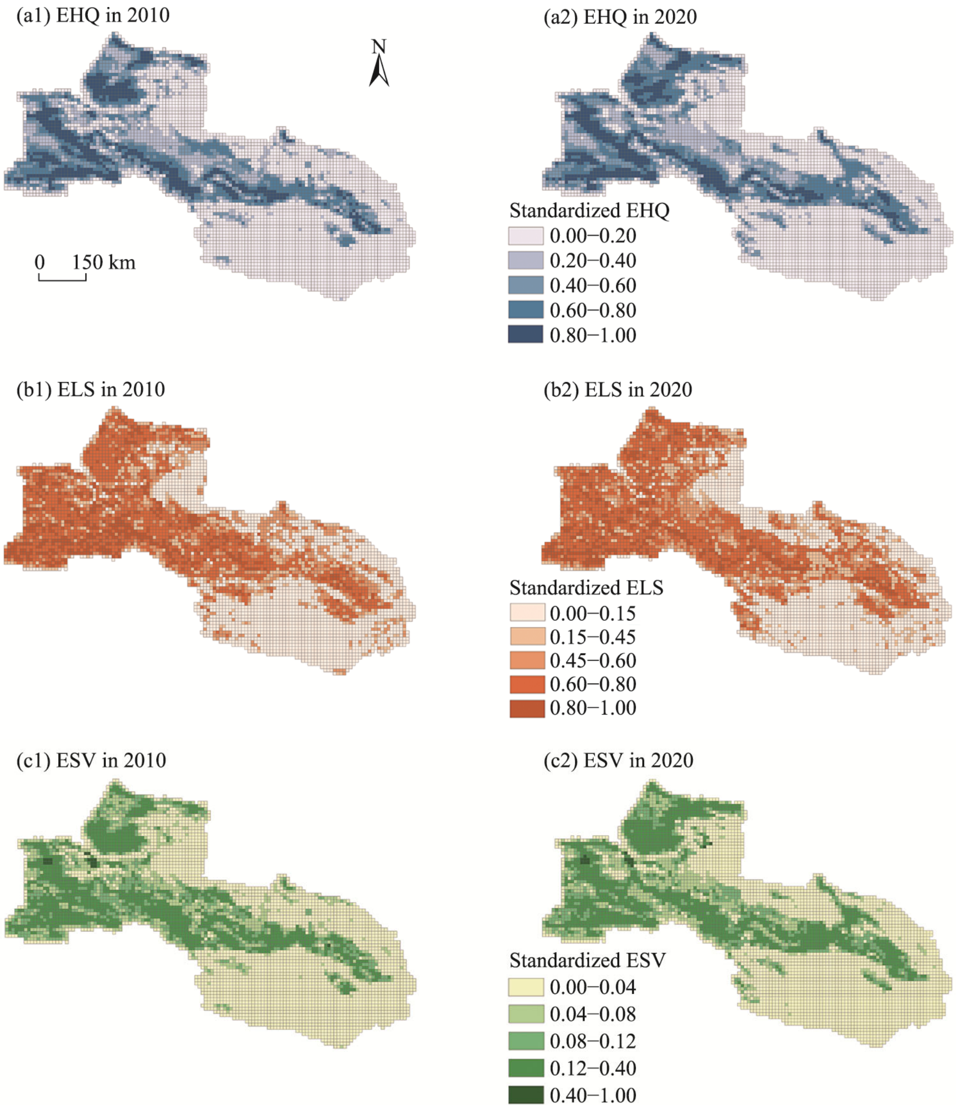

Fig. 4 Spatial distribution of EHQ (a1 and a2), ELS (b1 and b2) and ESV (c1 and c2) in the EBNSTM in 2010 and 2020. EHQ, ecosystem habitat quality; ELS, ecosystem landscape stability; ESV, ecosystem service value.

Table 3 Habitat suitability and sensitivity to the threat factors for the 24 second-level classes of land use types

Land use type	Habitat suitability	Sensitivity to threat factors			
		Cultivated land	Urban land	Rural residential land	Other construction land
Paddy field	0.5	0.3	0.8	0.6	0.7
Dryland	0.5	0.3	0.8	0.6	0.7
Forest	1.0	0.8	0.9	0.8	0.8
Shrubbery	1.0	0.5	0.8	0.6	0.6
Open forestland	0.8	0.7	0.9	0.8	0.8
Other forestland	1.0	0.8	0.9	0.8	0.8
High coverage grassland	0.9	0.5	0.7	0.6	0.6
Medium coverage grassland	0.8	0.6	0.7	0.6	0.6
Low coverage grassland	0.7	0.6	0.8	0.7	0.7
River canal	0.9	0.5	0.9	0.7	0.8
Lake	1.0	0.5	0.9	0.7	0.8
Reservoir pond	0.9	0.5	0.9	0.7	0.8
Glacier	0.1	0.2	0.3	0.2	0.2
Shoaly land	0.6	0.6	0.9	0.8	0.9
Urban land	0.0	0.0	0.0	0.0	0.0
Rural residential land	0.0	0.0	0.0	0.0	0.0
Other construction land	0.0	0.0	0.0	0.0	0.0
Desert	0.1	0.2	0.3	0.2	0.2
Gobi	0.1	0.2	0.3	0.2	0.2
Saline and alkaline land	0.1	0.2	0.3	0.2	0.2
Marsh	0.6	0.6	0.9	0.8	0.9
Bare land	0.1	0.2	0.3	0.2	0.2
Bare rock land	0.1	0.2	0.3	0.2	0.2
Other unused land	0.1	0.2	0.3	0.2	0.2

Table 4 Threat factors and their weights as well as the maximum impact distance

Threat factor	Weight	Maximum impact distance (km)	Decay type
Cultivated land	0.6	6	Exponential
Urban land	1.0	10	Exponential
Rural residential land	0.6	8	Exponential
Other construction land	0.7	9	Exponential

2.3.2 Assessment of ecosystem landscape stability (ELS)

In this study, we evaluated ELS based on landscape connectivity and heterogeneity using Fragstats 4.2 (McGarigal et al., 2023). Landscape connectivity is determined by the connectivity of important ecological patches and the connectivity of the whole landscape (Wu et al., 2010; Peng et al., 2015). Forestland and grassland play important ecological functions in the EBNSTM; therefore, we selected the overall connectivity, forestland cohesion and grassland cohesion as indicators to represent landscape connectivity. The overall connectivity was characterized by CONTAG (a landscape contagion index, representing the agglomeration degree or extension trend of different patch types in the grid), and forestland cohesion and grassland cohesion were all characterized by COHESION (the cohesion index of a specific type of patch within the grid). Landscape heterogeneity is an important attribute that determines landscape structure and function, as well as the source that ensures ELS (Hlásny, 2003; Sklenicka and Pixova, 2004). Landscape diversity is a key indicator that reflects landscape heterogeneity; therefore, Shannon's diversity index (SHDI) was selected in this study to represent landscape heterogeneity. Combined

with previous research results (Xia et al., 2022), various indicators of landscape connectivity and landscape heterogeneity were weighted (Table 5). The calculation results after standardization are shown in Figure 4b1 and b2.

Table 5 Evaluation index system of ecosystem landscape stability (ELS) used in this study

First-order indicator	Second-order indicator	Landscape index	Weight
Connectivity	Overall connectivity	CONTAG	0.3
	Forestland cohesion	COHESION	0.2
	Grassland cohesion	COHESION	0.2
Heterogeneity	Landscape diversity	SHDI	0.3

Note: CONTAG, the landscape contagion index, representing the agglomeration degree or extension trend of different patch types in the grid; COHESION, the cohesion index of a specific type of patch within the grid; SHDI, Shannon's diversity index, representing the diversity of landscape within the grid.

2.3.3 Assessment of ecosystem service value (ESV)

Based on the principles and methods of ESV (Costanza et al., 1997), as well as the equivalent coefficients of ESV in China (Xie et al., 2008) and in similar areas (Zhang et al., 2020b; Pan et al., 2021; Guo et al., 2022), we obtained the equivalent coefficients of ESV for each land use type in the EBNSTM (Table 6). Ecosystem services are divided into 4 first-class types (including provision services, regulation services, support services and cultural service) and 11 second-class types, as shown in Table 6. Notably, the land use types used here are mainly based on the first-level classes. However, it should be noted that in the "water body" class in the study area, the ESV generated by the second-class glacier was much higher than that of other second-class land use types. Therefore, the equivalent coefficient of ESV for glacier was corrected, while the other second-class land use types in the "water body" class remained unchanged. The equivalent coefficient of ESV for each land use type was determined by the relative importance of its ESV to the economic value of farmland food production, and the economic value of natural food production per unit area of farmland per year was set as the value of one equivalent factor. According to the calculation method of equivalent factor value (Costanza et al., 1997; Xie et al., 2008), the economic value of a single equivalent factor in the study area was 3827.40 CNY/hm^2. Then, the ESV of each land use type in the EBNSTM was obtained (Table 7), and the ESV of the EBNSTM in 2010 and 2020 was calculated and standardized, as shown in Figure 4c1 and c2.

Table 6 Equivalent coefficient of ecosystem service value (ESV) for the 6 first-level classes of land use types in the EBNSTM

Ecosystem service		Equivalent coefficient of ESV					
First-class type	Second-class type	Cultivated land	Forestland	Grassland	Water body	Glacier	Unused land
Provision services	Food production	0.85	0.23	0.23	0.66	0.00	0.01
	Raw material production	0.40	0.54	0.34	0.37	0.00	0.03
	Water supply	0.02	0.28	0.19	5.44	2.16	0.02
Regulation services	Gas regulation	0.67	1.76	1.21	1.34	0.18	0.11
	Climate regulation	0.36	5.27	3.19	2.95	0.54	0.10
	Purify environment	0.10	1.57	1.05	4.58	0.16	0.31
	Hydrological regulation	0.27	3.81	2.34	63.24	7.13	0.21
Support services	Soil conservation	1.03	2.14	1.47	1.62	0.00	0.13
	Nutrient cycling	0.12	0.16	0.11	0.13	0.00	0.01
	Biodiversity	0.13	1.95	1.34	5.21	0.01	0.12
Cultural service	Aesthetic landscape	0.06	0.86	0.59	3.31	0.09	0.05

Note: EBNSTM, economic belt on the northern slope of the Tianshan Mountains. It should be noted that in the "water body" class in the study area, the ESV generated by the second-class glacier was much higher than that of other second-class land use types. Therefore, the equivalent coefficient of ESV for glacier was corrected and extracted separately from the "water body" class.

Table 7 ESV of the 6 first-level classes of land use types in the EBNSTM

Ecosystem service		ESV (CNY/hm^2)					
First-class type	Second-class type	Cultivated land	Forestland	Grassland	Water body	Glacier	Unused land
Provision services	Food production	3253.29	893.06	893.06	2506.95	0.00	38.27
	Raw material production	1530.96	2054.04	1314.07	1397.00	0.00	114.82
	Water supply	76.55	1058.91	727.21	20,821.05	8267.18	76.55
Regulation services	Gas regulation	2564.36	6736.22	4618.39	5109.58	688.93	421.01
	Climate regulation	1377.86	20,157.63	12,209.40	11,271.69	2066.80	382.74
	Purify environment	382.74	5996.26	4031.53	17,510.35	612.38	1186.49
	Hydrological regulation	1033.40	14,582.39	8943.35	242,025.52	27,289.35	803.75
Support services	Soil conservation	3942.22	8203.39	5626.28	6200.39	0.00	497.56
	Nutrient cycling	459.29	625.14	433.77	478.42	0.00	38.27
	Biodiversity	497.56	7476.18	5115.96	19,940.74	38.27	459.29
Cultural service	Aesthetic landscape	229.64	3278.80	2258.16	12,668.69	344.47	191.37

2.4 Spatial autocorrelation analysis

The global spatial autocorrelation index (Moran's *I*) was used to test the spatial autocorrelation of ecological resilience in the EBNSTM. When Moran's *I* is greater than zero, ecological resilience is positively correlated in space. The larger the index is, the stronger the agglomeration characteristics of ecological resilience are. When Moran's *I* is lower than zero, ecological resilience is negatively correlated in space. The smaller the index is, the stronger the spatial dispersion characteristics of ecological resilience are. Moran's *I* ranges from –1.0 to 1.0.

If the ecological resilience of the EBNSTM has significant agglomeration characteristics, the Moran's *I* of the local spatial autocorrelation (LISA) was used to analyze the spatial heterogeneity of ecological resilience. The spatial distribution map of LISA includes four types: high-high clusters (the ecological resilience values of the study unit and adjacent units are higher), high-low outliers (units with high ecological resilience values are surrounded by adjacent units with low ecological resilience values), low-high outliers (units with low ecological resilience values are surrounded by adjacent units with high ecological resilience values) and low-low cluster (the ecological resilience values of the study unit and adjacent units are lower).

2.5 Geographically weighted regression (GWR) model

The spatial differences in the impacts of PRE, TMP, ETP, MRD, NLI and PM2.5 concentration on the ecological resilience of the EBNSTM were analyzed using the GWR model (Brunsdon et al., 1998; Fotheringham et al., 2002; Páez and Wheeler, 2009). The projection coordinates were chosen as the coordinates of each grid center in the EBNSTM, the weight was determined using the fixed Gaussian function, the optimal bandwidth was determined by the Akaike information criterion (AIC) method, and the regression calculation was carried out by GWR4 software (National Centre for Geocomputation, National University of Ireland Maynoothand Department of Geography, Ritsumeikan University, Kyoto, Japan) (Nakaya et al., 2009; Brunsdon and Singleton, 2015). The structure of the GWR model is as follows:

$$U_i = \delta_0\left(h_i, l_i\right) + \delta_1\left(h_i, l_i\right)V_{i1} + \delta_2\left(h_i, l_i\right)V_{i2} + \cdots + \delta_k\left(h_i, l_i\right)V_{ik} + \theta_i \, , \tag{2}$$

where U_i represents the dependent variable interpretation value of grid i; (h_i, l_i) represents the geographical coordinates of grid i; $\delta_0(h_i, l_i)$ represents the intercept of grid i; $\delta_k(h_i, l_i)$ (k=1, 2, 3, 4, 5, 6) represents the regression parameter of the k^{th} independent variable at the center of mass (h_i, l_i) of grid i, and there are 6 independent variables in this study; V_{ik} represents the value of the k^{th} independent variable of grid i; and θ_i represents the random error term of grid i.

2.6 Statistical analysis

We conducted fishing net creation, land use data processing, and area extraction of various land use types in ArcGIS 10.4, as well as the preprocessing of variables such as PRE, TEM, ETP, NLI, MRD and PM2.5 concentration. We used the extreme value standardization method to generate the variables without dimension in Excel (Wang et al., 2022), and visualized the calculation results of ecological resilience using ArcGIS 10.4 and origin software. The regression coefficients between ecological resilience and various influencing factors were calculated with the help of GWR4 software, and the significance test was conducted according to the *P* values of *t* test given by the model operation results (Nakaya et al., 2009; Brunsdon and Singleton, 2015). The tested data were visualized in ArcGIS 10.4.

3 Results

3.1 Temporal and spatial variation characteristics of ecological resilience

According to the established ecological resilience assessment model, we calculated the ecological resilience levels of 5058 evaluation units in the EBNSTM in 2010 and 2020. To analyze the changing trend of ecological resilience, we classified the ecological resilience into 5 levels in ArcGIS: low (0.0000–0.1280), generally low (0.1280–0.2860), medium (0.2860–0.4080), generally high (0.4080–0.5240) and high (0.5240–1.0000) levels.

3.1.1 Temporal variation characteristics of ecological resilience

From 2010 to 2020, the ecological resilience level of the EBNSTM was improved, with an increase of 1.50% in the average ecological resilience (from 0.2732 to 0.2773). During the study period, evaluation units with low level of ecological resilience accounted for 34.62% of the total evaluation units on average, but its proportion decreased slightly by 1.54% from 2010 to 2020 (Fig. 5). The proportion of evaluation units with generally low level of ecological resilience in 2010 and 2020 was approximately 15.68% on average, which showed a slightly decreasing trend (a decrease of 0.08%). Evaluation units with medium level of ecological

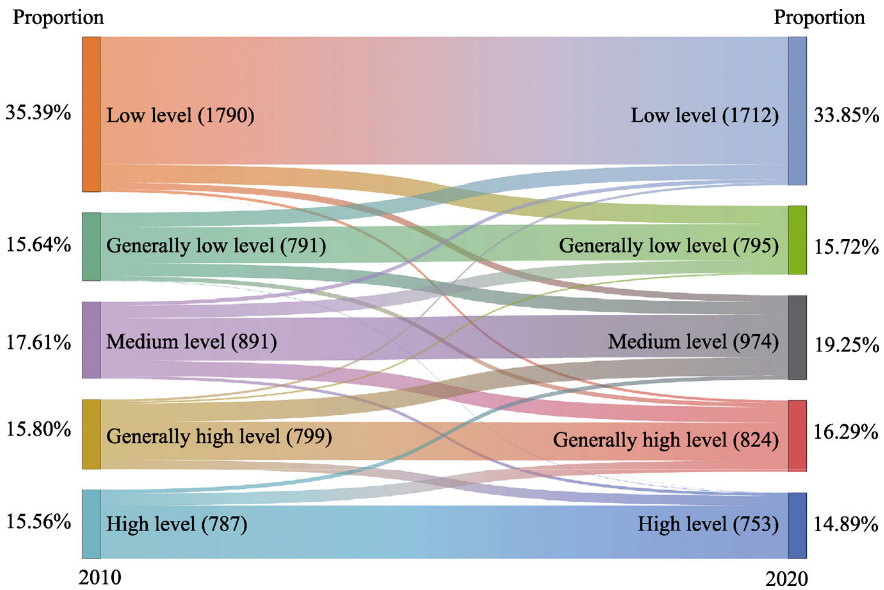

Fig. 5 Quantitative changes of ecological resilience levels in the EBNSTM from 2010 to 2020. The value in the parenthesis represents the number of evaluation units at each ecological resilience level for each year, and the proportion represents the percentage of evaluation units with each ecological resilience level in the total. The thickness of the line indicates the amount of change at each level from 2010 to 2020; the thicker the line, the greater the change.

resilience demonstrated an upward trend with an increase of 1.64% from 2010 to 2020, and its change range was the most obvious among the 5 levels. Evaluation units with generally high level of ecological resilience also showed an increasing trend, increasing by 0.49% during the study period. The proportion of evaluation units with high level of ecological resilience decreased by 0.67%. In terms of the variations in the number of evaluation units at different ecological resilience levels (Fig. 5), the number of evaluation units transforming from "low to high" level of ecological resilience was higher than the number of those transforming from "high to low" level of ecological resilience on the whole, indicating that the changes in ecological resilience showed a good trend overall. Based on the above analysis, in 2010 and 2020, evaluation units with low and generally low levels of ecological resilience accounted for about 50.00% of the total. Although there has been a transition from "low to high" level of ecological resilience, ecological resilience in the EBNSTM still needs to be further improved.

3.1.2 Spatial variation characteristics of ecological resilience

The spatial distribution pattern of ecological resilience in the EBNSTM in both 2010 and 2020 was "high in the western region and low in the eastern region", and the spatial differentiation was significant (Fig. 6a1 and a2). The areas with low and generally low levels of ecological resilience were primarily in the deserts and cities where human activities were concentrated. This was because these areas have poor habitat quality, low biodiversity and poor ecosystem stability due to adverse natural environments and human activities. The areas with medium level of ecological resilience were located in the oasis fringe areas outside the cities. Because the ecological environment outside the cities was relatively less disturbed by human activities, it formed a transition zone between low and high levels of ecological resilience. The areas with high and generally high levels of ecological resilience were located along the Tianshan Mountains, the Ili River Valley and the alpine areas in the northwest of the study area. These areas had high vegetation coverage, sufficient water resources, rich biodiversity, stable ecosystems, little influence from human activities and strong ability to absorb and transform external disturbances.

From the perspective of spatial change characteristics, the urban areas were the main regions showing the significant decline of ecological resilience with high level from 2010 to 2020. This was due to the rapid economic and social development in these areas during the past 10 years, the extremely high level of urban expansion and the increasing intensity of human production and life. These factors have led to many ecological problems, such as ecological risk increase, vegetation coverage reduction and habitat quality degradation, causing the areas with higher level of ecological resilience to contract. The areas where ecological resilience with low level improved significantly were concentrated in the desert and Gobi areas. The main reason was that a series of ecological civilization construction measures were implemented during the study period, such as ecological environment restoration, industrial transformation and upgrading, and energy structure adjustment, which brought about positive ecological and environmental effects, including the expansion of ecological land, the improvement of ecological environment and the increase in biodiversity.

In addition, the Moran's I of ecological resilience in the EBNSTM increased from 0.8021 to 0.8118 during 2010–2020, indicating a significant positive spatial correlation. Spatial clustering distribution phenomenon existed in the study area regardless of ecological resilience levels, and the spatial clustering trend was enhanced during the study period. The spatial agglomeration and heterogeneity characteristics of ecological resilience were further analyzed by combining the LISA (Fig. 6b1 and b2). The ecological resilience of the EBNSTM presented significant spatial clustering characteristics at high level or low level. The "high-high cluster" and "low-low cluster" were the main spatial correlation patterns. The "high-high cluster" areas were primarily zonally distributed along the Tianshan Mountains and clustered in the mountains of the western Junggar Basin in clumps. During the study period, the "high-high cluster" areas showed a decreasing trend in the northern slope of the middle Tianshan Mountains and the Ili River Valley. The "high-high cluster" displayed a diffusion phenomenon in the mountains of the western Junggar Basin's

mountainous region, and the high-value agglomeration phenomenon in the northern margin of the Turpan-Hami Basin was significantly enhanced. The "low-low cluster" areas were distributed in the desert areas of the Turpan-Hami Basin and the Junggar Basin in sheets and clumps. Over time, the areas with "low-low cluster" expanded obviously in the southern margin of the Junggar Basin, while the "low-low cluster" phenomenon in the Turpan-Hami Basin and its surrounding areas was somewhat diminished.

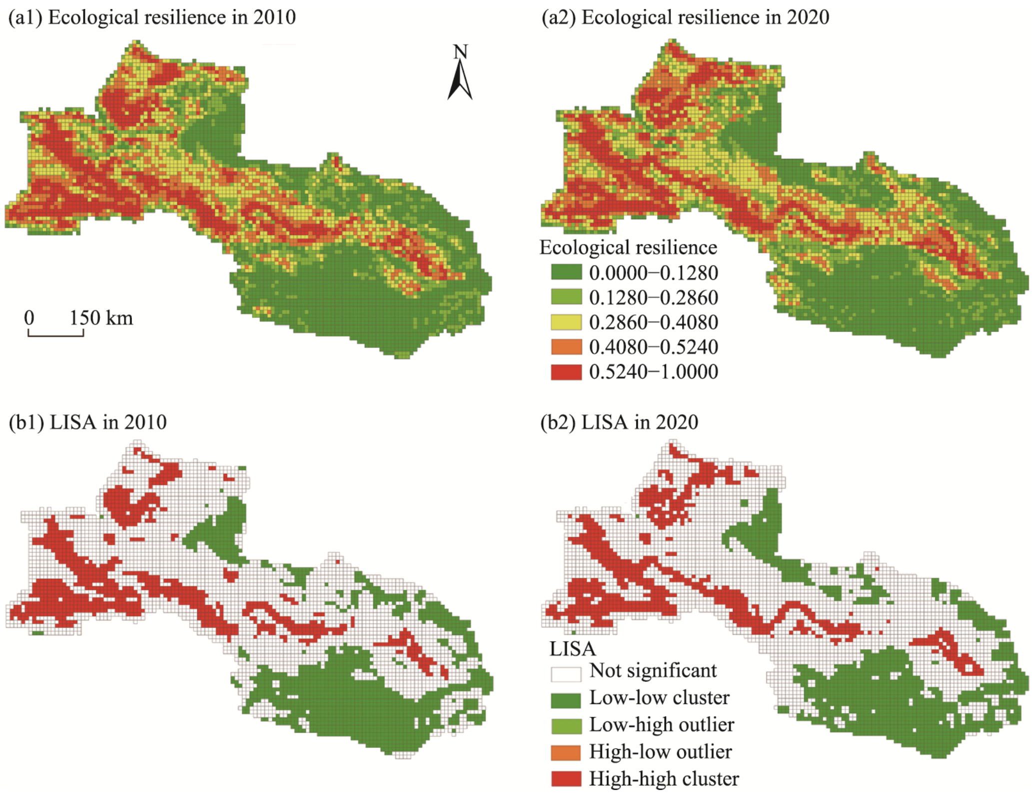

Fig. 6 Spatial distribution of ecological resilience (a1 and a2) and LISA (b1 and b2) in the EBNSTM in 2010 and 2020. LISA, the global spatial autocorrelation index (Moran's I) of the local spatial autocorrelation, showing the spatial heterogeneity of ecological resilience.

3.2 Impacts of climate change and human activities on ecological resilience

3.2.1 GWR model diagnosis

The traditional linear regression model based on the ordinary least squares (OLS) model only performs global estimation of parameters. If there is spatial autocorrelation among independent variables, it cannot reveal the relationship between variables under the action of space. The ecological resilience of the EBNSTM showed a significant positive spatial correlation and spatial heterogeneity. Before using the GWR model to explore the relationship between variables, it was necessary to compare the goodness of fit with the OLS model. Table 8 shows that the GWR model had lower values of sigma and corrected Akaike's information criterion (AICc) than the OLS model, and the values of model goodness of fit (R^2) and adjusted model goodness of fit (R_{adj}^2) for the GWR model were higher than those for the OLS model. Therefore, it was more explanatory to explore the relationship between ecological resilience and various factors by using the GWR model.

3.2.2 Regression results between ecological resilience and influencing factors

In this paper, the significance of regression coefficients between ecological resilience and influencing factors was examined using the t test, and the regression coefficients that passed the 5% significance level test were selected and statistically analyzed (Table 9). The inter-annual

Table 8 Comparison of parameters between the ordinary least squares (OLS) model and geographically weighted regression (GWR) model in 2010 and 2020

Parameter	2010		2020	
	OLS model	GWR model	OLS model	GWR model
Sigma	0.173	0.118	0.172	0.110
AICc	–3374	–7050	–3449	–7743
R^2	0.513	0.787	0.500	0.807
$R_{adj}{}^2$	0.512	0.773	0.499	0.794

Note: AICc, corrected Akaike's information criterion; R^2, model goodness of fit; $R_{adj}{}^2$, adjusted model goodness of fit.

Table 9 Statistical results of regression coefficients between ecological resilience and influencing factors from the GWR model in 2010 and 2020

Influencing factor	Regression coefficient							
	Minimum		Maximum		Mean		Standard deviation	
	2010	2020	2010	2020	2010	2020	2010	2020
TMP	–14.16	–10.95	9.39	5.62	0.76	0.57	3.26	3.06
PRE	–11.19	–8.60	28.78	60.66	0.37	1.27	3.93	6.41
ETP	–5.55	–5.55	6.55	7.02	–1.58	–1.36	1.94	1.98
MRD	–1.62	–1.97	1.06	0.57	–0.36	–0.61	0.50	0.36
NLI	–28.64	–35.40	119.54	58.89	5.01	1.92	14.96	12.99
PM2.5 concentration	–4.21	–3.25	2.77	3.40	0.17	–0.26	1.12	1.18

Note: MRD, distance to the main road.

variations of regression coefficients were large, and the regression coefficients could be positive or negative, indicating that the correlation between ecological resilience and each influencing factor was not stable. On the mean, from 2010 to 2020, the impacts of NLI, TMP and ETP on ecological resilience decreased significantly, while the impacts of PRE and MRD on ecological resilience increased significantly. For PM2.5 concentration, the mean regression coefficient changed from positive to negative. The standard deviation of regression coefficients for NLI was the largest, indicating that the impact of NLI on ecological resilience showed significant regional difference; while the standard deviation of regression coefficients for MRD was the smallest, showing little spatial difference in its impact on ecological resilience. Significant increase in the standard deviation of regression coefficients for PRE indicated that the regional difference in the impact of PRE on ecological resilience became more obvious.

3.2.3 Impact of influencing factors on ecological resilience

Figures 7 and 8 provide a more visual illustration on the regional heterogeneity of the impacts of each influencing factor on ecological resilience. TMP mainly presented a positive correlation with ecological resilience in the oasis areas with low temperature, and a negative correlation with ecological resilience in the desert fringe areas with high temperature. Therefore, appropriate temperature conditions were conducive to improving regional ecological resilience. However, both the positive and negative regression coefficients between ecological resilience and TMP reduced significantly, indicating that the impact of TMP on ecological resilience in these areas gradually weakened (Table 9; Fig. 7a1 and a2).

PRE was a key positive factor affecting ecological resilience in most areas of the EBNSTM. The positive impact of PRE on ecological resilience significantly increased during 2010–2020, with the mean regression coefficients increasing from 0.37 to 1.27. From the perspective of spatial heterogeneity (Fig. 7b1 and b2), the areas with high positive regression coefficients were mainly concentrated in the desert fringe areas of the Turpan-Hami Basin with relatively low precipitation, while the regression coefficients in the areas of the Ili River Valley and the Tianshan Mountains with abundant precipitation were relatively low. Generally speaking, precipitation improved

ecological resilience in most regions, especially in the areas with relatively low precipitation.

ETP showed an obvious negative influence on ecological resilience overall, and the mean regression coefficients slightly decreased during the study period (Table 9). Ecological resilience in the areas of the Ili River Valley and the middle Tianshan Mountains was most strongly affected by ETP, and the negative influence gradually weakened from the center to the periphery of the areas with high vegetation coverage and good hydrological conditions; however, a few areas with positive regression coefficients or extremely low negative values were distributed in the desert-oasis transition zones (Fig. 7c1 and c2). ETP was the main factor blocking the

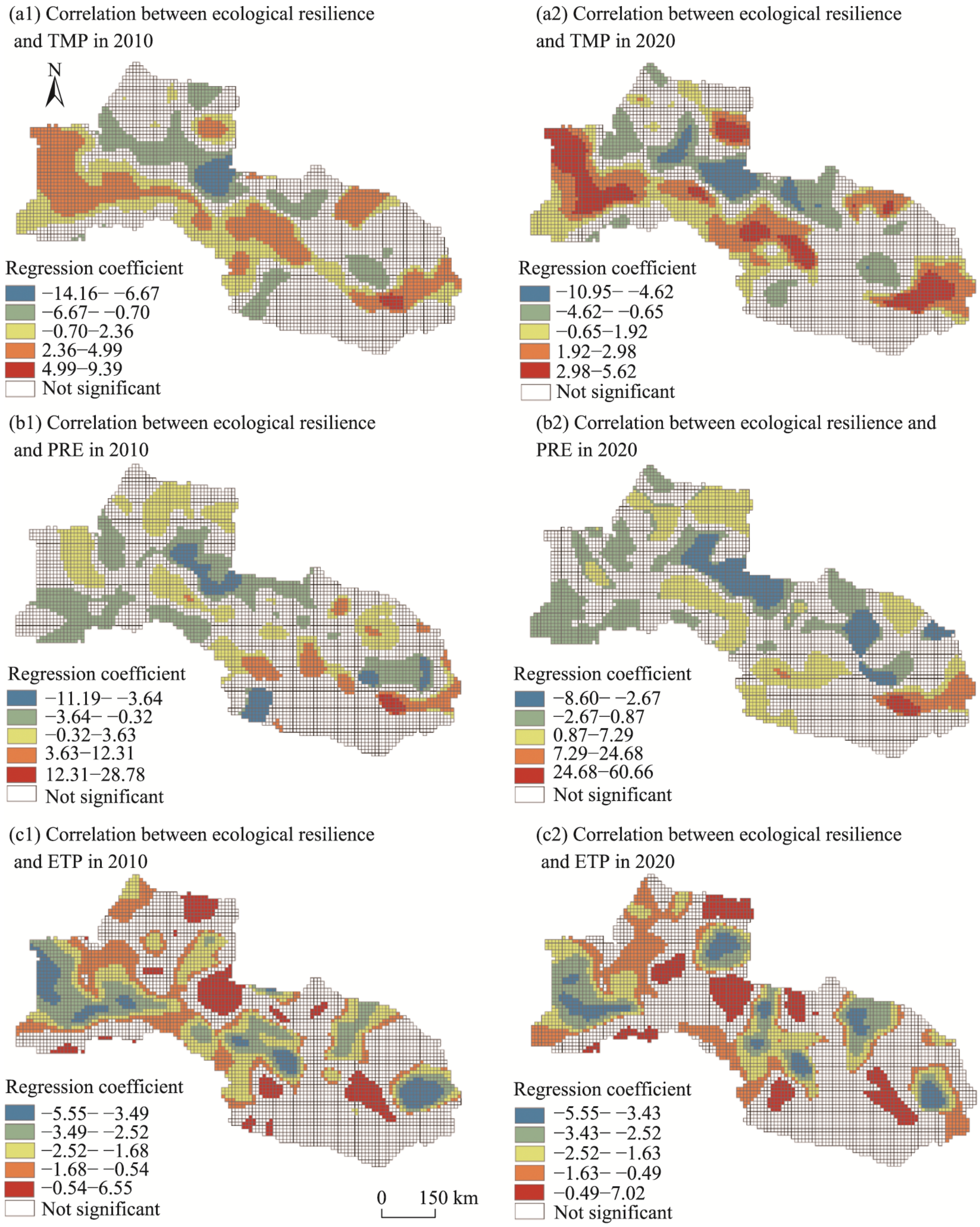

Fig. 7 Spatial distribution of regression coefficients between ecological resilience and climate factors in 2010 and 2020. (a1 and a2), correlation between ecological resilience and TMP; (b1 and b2), correlation between ecological resilience and PRE; (c1 and c2), correlation between ecological resilience and ETP.

improvement in regional ecological resilience, and the blocking effect was more obvious in the areas with better ecological environment.

MRD had a negative impact on ecological resilience in most regions, and the areas with great negative impact showed an obvious expansion trend (Fig. 8a1 and a2). At the beginning of the study period (2010), the areas with great negative impact of MRD on ecological resilience were mainly distributed in the western margin of the Junggar Basin, part of the Tianshan Mountains and the Turpan-Hami Basin, while the areas with positive impact or very small negative impact were distributed in Urumqi City, Turpan City, Karamay City, counties (cities) direct under Ili Kazak Autonomous Prefecture, and other cities with good traffic conditions. This showed that the

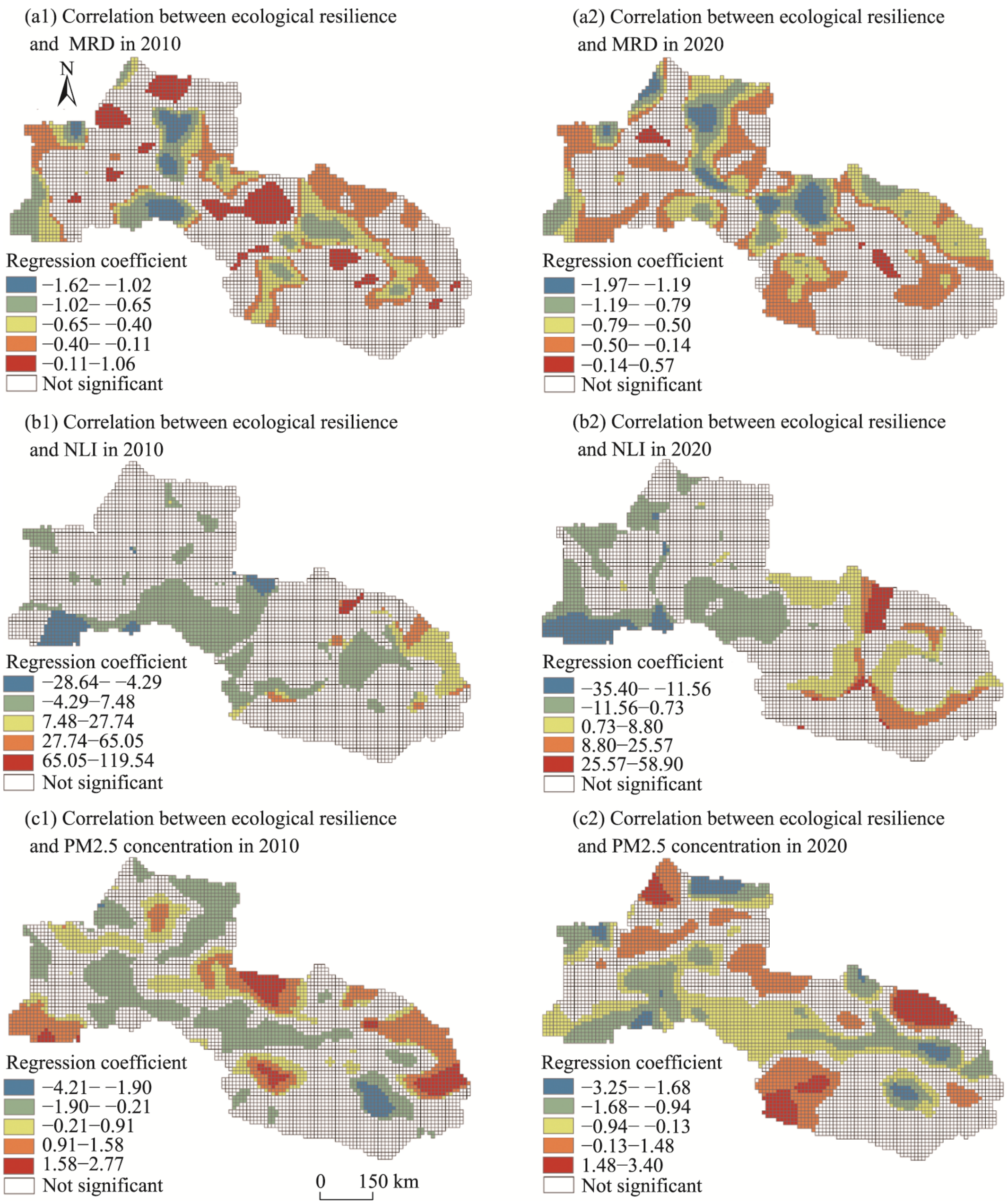

Fig. 8 Spatial distribution of regression coefficients between ecological resilience and human activity factors in 2010 and 2020. (a1 and a2), correlation between ecological resilience and MRD; (b1 and b2), correlation between ecological resilience and NLI; (c1 and c2), correlation between ecological resilience and PM2.5 concentration.

further away human activities were from the desert and mountainous areas during this period, the less they contributed to the improvement of ecological resilience, while the opposite was true in more urbanized areas. At the end of the study period (2020), the negative impact of MRD on ecological resilience in northern Hami City became more obvious. The negative impact of MRD on ecological resilience in cities such as Urumqi City was significantly enhanced, and these cities gradually became high-value areas of negative impact, indicating that at the end of the study period, the impact of MRD on ecological resilience did not change in the desert and mountainous areas, while in the urbanized areas, the impact changed under the influence of human activities, such as the implementation of environmental protection policies.

The impact of NLI on ecological resilience was positive overall, but its impact was significantly weakened over time (Table 9; Fig. 8b1 and b2). The areas with negative regression coefficients between ecological resilience and NLI were primarily distributed in the western part of the study area where the ecological environment was better, which showed an expansion trend. The areas with positive regression coefficients were mainly distributed in the eastern part with poor natural conditions and low economic and social development intensity. The areas with positive impact of NLI on ecological resilience showed an expansion trend, but the regression coefficients decreased. In the areas where the natural background conditions were better, the development intensity had a blocking effect on ecological resilience. Economic and social development has led to a decrease in forestland, grassland and other ecological landscapes. In contrast, under harsh natural background conditions, economic and social development could promote ecological resilience. Economic and social development promoted the investment in ecological governance of deserts and Gobi, effectively improving the local ecological resilience.

The mean regression coefficients between ecological resilience and PM2.5 concentration changed from positive to negative (Table 9). This indicated that water pollution, soil pollution, air pollution and other environmental problems caused by the industrialization process blocked the improvement of ecological resilience overall during the study period, but the spatial heterogeneity was obvious (Fig. 8c1 and c2). In the relatively developed cities or urban agglomeration areas such as Urumqi City, Karamay City and Hami City, negative correlation between ecological resilience and PM2.5 concentration was found, but the negative impact was significantly weakened, indicating that the blocking effect of industrialization on ecological resilience in these areas showed a decreasing trend. This may because that the transformation and upgrading of traditional industries as well as the development and expansion of emerging industries have weakened the problem of industrial pollution. In the desert and Gobi areas with harsh natural environment conditions, PM2.5 concentration was positively correlated with ecological resilience, and the positive impact degree was significantly enhanced during the study period. Investment in infrastructure construction, environmental protection, and science and technology brought by industrialization could effectively improve ecological resilience in these areas. In particular, the construction of water conservancy facilities, green space, etc., has improved the poor natural background and the level of ecological resilience in the desert and Gobi areas.

4 Discussion

4.1 Characteristics of ecological resilience and its responses to climate change and human activities

In terms of the spatial distribution characteristics of ecological resilience, the structure and characteristics of the natural ecosystem composed of "mountain-oasis-desert" shaped the overall spatial distribution pattern of ecological resilience in the EBNSTM, which was consistent with the findings of research on habitat quality (Bai et al., 2019; Dong et al., 2022; Wei et al., 2022b), ecosystem services (Guo et al., 2022) and ecological environment quality (Yan et al., 2021; Aizizi et al., 2023; Long et al., 2023) in arid and semi-arid areas. That is, the areas with higher vegetation coverage and better climate conditions will have better habitat quality, higher ESV and

better connectivity of important ecological landscapes. The difference in human activity intensity was also an important factor affecting the regional distribution difference of ecological resilience (Tong et al., 2023). The rapidly urbanized areas, urban fringe areas, and areas without or with less human disturbance showed different levels of ecological resilience. The reason was that in the areas with high population density and rapid urbanization processes, ecosystems were subjected to stronger destruction and impact, and the ecological environment quality, soil and water conservation function, and landscape stability were far worse than those in the areas with slower urbanization processes (Fahrig, 2003; Pan et al., 2022b).

The impacts of climate change and human activities on ecological resilience showed obvious spatial heterogeneity, which was consistent with the results reported by Pan et al. (2022b). The areas greatly affected by climate conditions are mainly concentrated in the alpine forestland and grassland areas, because changes in precipitation, temperature, and evapotranspiration directly affect the material circulation process of ecosystems and then affect the biodiversity and vegetation growth of these regions (Valayamkunnath et al., 2018; Guo et al., 2022; Liu et al., 2023). Change in land use was the direct impact of human activities on ecological resilience (Cai et al., 2012; Bai et al., 2019; Tong et al., 2023). The degradation of habitat quality, the reduction in landscape connectivity and the weakening of ecological service function caused by the encroachment of ecological land due to the increasing intensity of human activities are the direct factors that damage the functional integrity and structural stability of ecosystems (Gashaw et al., 2018), while the implementation of ecological restoration projects is the key to improving the quality of regional ecological environment (Long et al., 2023).

Overall, the response of ecological resilience to climate change may not be significant in the short term, while its response to changes in human activities is more significant in the short term (Gonzalez et al., 2010; Pan et al., 2022b). In particular, in the past decade, the expansion of built area, the increase in industrial land and the construction of transportation networks in the EBNSTM have put much pressure on ecological land such as forestland, grassland and water body (Yan et al., 2021; Aizizi et al., 2023). However, the increased vegetation coverage and the control of desertification due to the implementation of ecological and environmental projects (i.e., the Three-North Shelterbelt Program) and the construction of nature reserves have played a significant role in improving the overall ecological environment of the region (Lu et al., 2018; Jing et al., 2020; Long et al., 2023). This was an important reason why ecological resilience in the EBNSTM has maintained a stable trend under the influence of the continuous increase in human activities.

4.2 Suggestions for improving ecological resilience in arid and semi-arid areas

Based on the results of ecological resilience in the EBNSTM, this paper proposes some suggestions for improving ecological resilience in arid and semi-arid areas. First, environmental protection should adhere to respecting, complying with and protecting nature, to ensure the integrity of natural ecological landscapes such as rivers, lakes, glaciers, forests and grasslands, and to strictly protect natural ecological sources and ecological corridors. Second, ecological restoration projects (such as water storage and sand prevention and control) should be accelerated in the desert and Gobi areas with low ecological resilience. Third, green space construction should be strengthened in the rapidly urbanized areas, urban development boundaries should be intensively and greenly demarcated and strictly controlled, and the overexploitation of groundwater should be strictly prohibited. Ecological resilience should be enhanced by improving vegetation coverage, increasing landscape diversity and optimizing water and soil resource allocation. Moreover, importance should be attached to ecological environmental protection in the urban or oasis fringe areas. To return farmland to forests, afforestation, ecological forest cultivation and other measures should be implemented to build shelterbelts and ecological protection barriers to cushion the impact and pressure of social and economic activities on the ecological environment. Finally, the technological transformation and upgrading of traditional industries need to be accelerated to continue to control the ecological pollution problems caused by industrialization.

4.3 Limitations and research prospects

First, land use data serve as the basis of the ecological resilience assessment model. Although this model could reflect the natural background characteristics of regional ecosystems in water conservation, climate regulation, biodiversity and other aspects to a certain extent, it still had subjective experience in the characterization process (Bai et al., 2019; Fang et al., 2022). Therefore, restricted by the availability and applicable scale of data, the role of economic and social systems in ecological resilience was not considered in the assessment model, and the impact of hidden human activities such as culture and policy on ecological resilience was ignored (Clements et al., 2021; Li et al., 2021). In the future, research units can be divided according to administrative divisions to make full use of macroeconomic statistical economic and social data, and to explore the mechanism of ecological resilience based on the complexity of society-economy-ecosystem. Third, topographic factors such as elevation and slope are key variables affecting vegetation growth and animal habitat (An et al., 2018; Guo et al., 2022). Topographic differences will lead to significant differences in water and soil conservation in different regions, especially in mountain ecosystems (An et al., 2018; Guo et al., 2022). The impact of topographic factors on ecological resilience should be explored and discussed in the future. Finally, multi-scale studies on ecological resilience of different landforms (i.e., mountains, oases and deserts), different river basins, multiple water collection types (i.e., underground water collection types and surface water collection types), or different functional areas (i.e., rapid urbanization areas, urban and rural transition areas, rural areas, key ecological functional areas and oasis fringe areas), can be carried out in the future. Differences in ecological resilience and the impact of human activity factors at different scales can be explored to determine the scale effect.

5 Conclusions

In this study, we analyzed the temporal and spatial variation characteristics of ecological resilience in the EBNSTM from 2010 to 2020, and evaluated the responses of ecological resilience to climate change and human activities using the GWR model. The following conclusions are drawn:

(1) The ecological resilience of the EBNSTM showed an upward trend during 2010–2020, with the average value increasing from 0.2732 to 0.2773, but the low level of ecological resilience was still dominant.

(2) The ecological resilience of the EBNSTM showed a spatial pattern of "high in the western region and low in the eastern region". The areas with low level of ecological resilience were mainly distributed in the desert, Gobi and rapidly urbanized areas, and the ecological resilience was improved from 2010 to 2020. The regions with high or generally high level of ecological resilience were in the valley and mountainous areas, but these regions contracted significantly from 2010 to 2020.

(3) The spatial agglomeration of ecological resilience in the EBNSTM showed an enhanced trend, the Moran's I increased from 0.8021 to 0.8118, and the "high-high cluster" and "low-low cluster" were the main local spatial autocorrelation patterns of ecological resilience in the EBNSTM.

(4) Among the climate factors, the impact of TMP on ecological resilience decreased significantly over time. PRE was the key factor promoting ecological resilience, which improved ecological resilience in most areas, and the enhancement effect was more obvious in the areas with scarce precipitation. ETP was the main climate factor blocking ecological resilience, and its blocking effect was most obvious in the areas with better ecological conditions.

(5) Among the human activity factors, MRD had a negative impact on ecological resilience in most areas, indicating that the further the distance from human activities, the more unfavorable the improvement of ecological resilience to some extent. The regression coefficients of ecological

resilience with NLI and PM2.5 concentration showed relatively similar spatial distribution characteristics. In the areas where the natural background conditions were better, the economic and social development intensity had a blocking effect on ecological resilience. In contrast, under the harsh natural background conditions, economic and social development could promote ecological resilience.

The findings of this study can provide a scientific reference for the ecological environment protection of the EBNSTM and sustainable development in arid and semi-arid areas.

Conflict of interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Author contributions

Conceptualization: ZHANG Shubao; Methodology: ZHANG Shubao, LEI Jun, TONG Yanjun; Data curation: ZHANG Shubao, LU Danni, FAN Liqin; Writing - original draft preparation: ZHANG Shubao; Writing - review and editing: ZHANG Shubao, LEI Jun, ZHANG Xiaolei; Funding acquisition: LEI Jun, DUAN Zuliang; Visualization: ZHANG Shubao, LU Danni, FAN Liqin; Supervision: LEI Jun, ZHANG Xiaolei, DUAN Zuliang.

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